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OPTIMIZATION OF A VALVE USING A GENETIC ALGORITHM

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ABSTRACT

A numerical optimization of the suction valve of a large reciprocating compressor has been carried out as a case study, using a combination of a compressor simulation program and a genetic optimization algorithm. This optimization algorithm is based on the theory of biological evolution: survival of the fittest. The compressor simulation program solves the mass and energy conservation laws for the suction chamber, cilinder and discharge chamber. The dynamics of the valves are described by Newtonian motion and the piping system is partly taken into account as flow restrictions.

A set of optimal designs has been generated by assigning different combinations of weight factors to the volumetric efficiency, the isentropic efficiency and the impact velocity of the valve. These performance data were used for judging the compressor quality. This procedure can be applied as an effective design tool when a considerable number of parameters is involved, especially when analytical optimization is either impossible or too complex.

INTRODUCTION

The object of the investigation presented here is to establish the feasibility of numerical optimization as a design tool for reciprocating compressors. The work is done in a co-operation between Grasso Products B.V. and the Delft University of Technology. As the subject of this case study the suction valve of the Grasso RC11 compressor was chosen, mainly because detailed geometrical and experimental data were available. The genetic optimization algorithm was selected because the only constraint it imposes, on the function it optimizes, is that it exists and because it does not get trapped by local optima: it always searches for the global optimum.

PARAMETERS AND OBJECTIVE FUNCTION

The suction valve of the RC11 is a ring valve (fig. 1). The geometry can therefore be defined by the thickness (h_v), the inner diameter (d_v) and the outer diameter (D_v). The inner diameter depends on the cylinder diameter and is therefore not a parameter. The thickness itself is not an input parameter for the compressor model, but it is added as an independent parameter in order to describe the volume and mass of the valve. The valve is loaded with sinusoidal springs, which can be represented by an exponential characteristic (fig. 2). It is parameterized by the force (F_{min}) at zero lift and the force (F_{max}) at maximum lift (x_{max}). Table 1 shows the parameters and their ranges.

Parameter	RC11	Range	Unit
D_v	200	180...240	mm
h_v	1.0	0.5...5.0	mm
x_{max}	2.6	1.5...4.0	mm
F_{min}	18	10...40	N
F_{max}	137	40...240	N

Tab. 1 *The parameters with their values for the RC11 compressor and the ranges used during optimization.*

These parameters will be fed into the compressor simulation program, which calculates the performance data that are used to judge the quality of the compressor.

Initially an economic optimization was intended. It should minimize the total costs of operation including depreciation, interest, energy requirements and costs of maintenance. But the economical optimization was abandoned because it turned out that the quantification of some costs was too complex. As an alternative a technical judgement is used, constructed of three quantities: the isentropic efficiency (η), the volumetric efficiency (λ) and the maximum impact velocity of the suction valve (v_{max}). The latter was added because it is the main influence on the lifespan of the valve (Zuidema [9]). Since the optimization algorithm requires a single value judgement, weight factors (a, b, c) where used to combine these quantities in a so called *objective function*:

$$f_{objective} = a\lambda + b\eta + c\left(1 - \frac{v_{max}}{v_{ref}}\right) \quad ; \quad a + b + c = 1 \tag{1}$$

The impact velocity is made dimensionless by scaling it with a reference (v_{ref}) in order to make it comparable with the efficiencies. The negative sign is needed because it should be minimized while the efficiencies must be maximized.

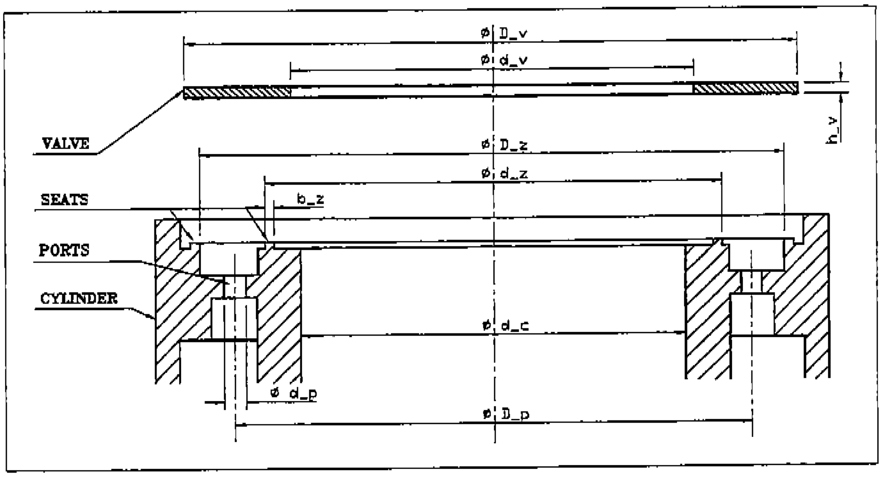

Fig. 1 *The construction of the part of the cilinder where the suction valve is located, including the symbols of the geometrical data.*

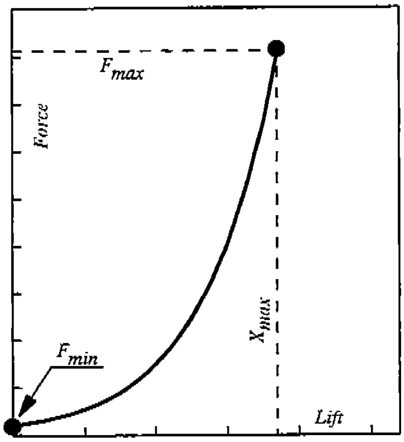

Fig. 2 *The exponential characteristic of the springs.*

Since the numerical value of the objective function is of no importance (only the location of the maximum is required) one of the weight factors is superfluous. This allows stating a relation between them, decreasing the number of independencies. Here the sum always equals one.

SOFTWARE

The compressor performance prediction is executed by a computer program based on the mathematical compressor model first introduced by Blankespoor and Touber [1] and described in more detail by Touber [7] and Touber et.al. [8]. The model consists of a set of six coupled first order differential equations describing the pressure and specific volume changes of the process gas in the cylinder, suction and discharge chambers of reciprocating compressors. These equations result from the application of the energy and mass conservation laws for these three system components. The gas is assumed ideal. Further, the motion of the automatic valves is described by two first order differential equations. These equations describe Newton's second law for a mass-spring system with a single degree of freedom. The force acting on the valve is the resultant of the gas force, the spring force and the damping force. In the model the gas force coefficient is allowed to vary with geometry while the damping force coefficient is considered independent of geometry. In the transition from closed to open conditions a fourth force is assumed to apply: the sticktion force. This force will also be geometry dependent.

The model further includes a set of four equations describing the mass flow through the valves and the suction and discharge piping systems. The mass flow in these four equations follows a quasi steady-state model assumption. These mass flows are then non-constant coefficients in the differential equations named above. The pressure in the suction and discharge connections is superimposed on the model.

The model has been implemented in C. Heun's method has been used for the numerical integration of the set of differential equations. An adaptive time step size has been used to guarantee accuracy and small computing times. In addition to the time (or crank angle) dependent variables as cylinder pressure and valve lift, the output of the compressor computer model includes the performance data required for optimization purposes: the isentropic and volumetric efficiencies and the valve impact velocity.

The parameters do not form a class by themself: *e.g.* when the valvelift is increased, the clearance volume must also increase. This requires a generic model for the relations between the parameters and:

- the clearance volume,
- the flow resistance,
- the valve sticktion force coefficient,
- the gas force coefficient,
- the mass of the valve,
- the number of ports,
- various geometrical data of the compressor.

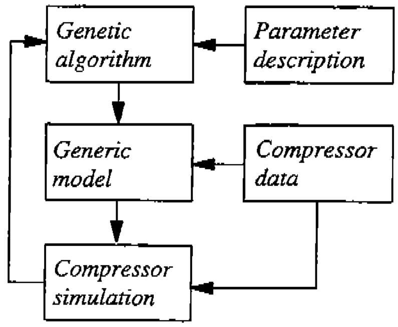

Fig. 3 *Chart of the optimization program. The left side represents the software. It is executed in an infinite loop.*

The relations for the sticktion force coefficient and the gas force coefficients were taken from Touber [7]. The relations for the geometrical data and the mass of the valve are shown in table 2.

Constants: d_z, d_c, b_z, d_k Parameters: D_v, h_v

Property	Symbol	Keeping constant	Formula
diameter outer seat	D_z	overlap	$D_v - D_z$=constant
diameter ports	d_p	extra width	$(D_z - d_z)/2 - d_p$ =constant
number of ports (rounded)	n_p	remaining material	$\pi D_p/(\pi D_p - n_p d_p)$ =constant
mass valve	m	specific mass	$m = \pi \rho h_v (D_v^2 - d_v^2)/4$

Tab. 2 *The generic model assumes that certain properties remain constant, that is they have the same value (independent of parameters) as the RC11 compressor. This results in formulae for the dependent dimensions.*

The flow resistance (ξ) required additional theoretical work. A model was adapted, which assumes three serial resistances:

- the gap between the valve and its seat, only dependent on the lift (indexed v),
- the ports which are modelled as orifices, the resistance is a function of the area ratio and was taken from the DIN 1952 standard [3] (indexed p),
- all other sources for which the resistance is not dependent on the parameters (indexed $*$).

The pressure drop between the suction pipe and the cylinder can then be calculated, assuming a constant value of the specific mass (ρ):

$$\Delta p = \frac{1}{2}\rho c_v^2 \left[\xi_v + \xi_p \frac{A_v^2}{A_p^2} + \xi_* \frac{A_v^2}{A_*^2}\right] \tag{2}$$

Here all resistances are taken with respect to the velocity in the gap (c_v) by scaling the velocity with the flow area's. The value of ξ_v must tend to zero when the lift increases infinitely. From a comparison with measurements by Houët [Grasso Products B.V.], this appeared only possible when the value of ξ_*/A_*^2 is within 4% of 2.65×10^{-6} mm^{-4}.

A chart of the entire program is shown in fig. 3. The genetic algorithm generates sets of parameters and feeds them into the generic model. This will set all input data for the compressor simulation program and start the calculations. The result of the simulation, the value of the objective function, will be fed back into the genetic algorithm which will use it to effectively generate new sets of parameters. This procedure will be repeated until the user terminates it (normally it will be continued while the values of the optimal parameters have not stabilized).

GENETIC ALGORITHM

It is clear that in the preceding sections the problem has been formulated as an optimization problem. The objective is to find the values of the parameters (table 1) that give rise to a maximum value of the objective function (eq. 1). To solve this problem, the optimization program GOOD (Generator Of Optimal Designs) has been used, which was developed at the Delft University of Technology. This program [5] is based on Monte Carlo methods and genetic algorithms. In this program the objective function has to be programmed as a subroutine, and the parameters and their ranges are given in an input file.

A genetic algorithm is a simulation of the evolution theory and employs the principle of survival of the fittest. In searching an optimum, sets of solutions are used instead of one solution. Such a set is called a population. A start population is created by randomly generating values for the independent variables. For all members of the population the objective function (also called fitness function) is evaluated, and the members are sorted on ascending order of fitness. A new population is created from this population. This is done in such a way that the good qualities of a population are inherited by the members of a new population. It appears that the new populations tend to have better values for the fitness function. Davis [2], Goldberg [4] and Michalewicz [6] describe various methods for this process. In GOOD the newly found optima are drawn on the screen with the aid of graphic functions, in such a manner that it can be seen in what regions of the parameter ranges the suboptima are found. By interactively modifying those ranges, completely new and better populations can be created. In this way premature convergence can be avoided. Moreover several parameters governing the optimization process, like the population size can be modified during run time.

RESULTS

Using this setup, a set of different optimal designs have been generated using the working conditions of tabel 3. In table 4 some results are presented. Since the isentropic efficiency is very sensitive for the flow resistance, the maximum lift become larger when its weight factor (b) increases. But since this effect also increases the clearance volume, the volumetric efficiency decreases (fig. 4...7). It appears, from the fact that the outer diameter and the forces of the springs show irregular variations, that these parameters are not critical. The influence of the impact velocity on the optimal design is considerable. Comparison of the left and right side of the table 4 shows that, when the impact velocity is taken into account:

Property	Value	Unit
Evaporating temperature	-10	°C
Condensating temperature	35	°C
Superheating	5	°C
Rotational speed	1000	rpm
Refrigerant	R 22	-

Tab. 3 *Working conditions.*

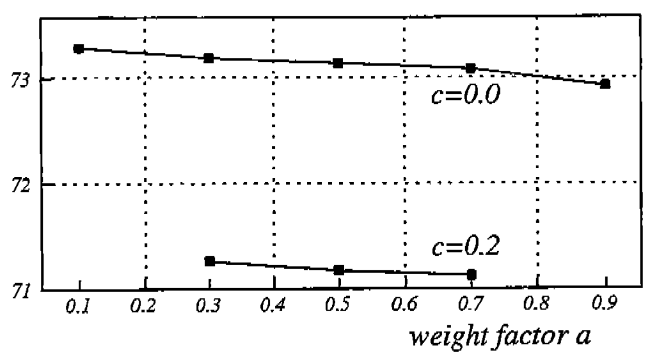

Fig. 4 *The isentropic efficiency as a function of the weight factors.*

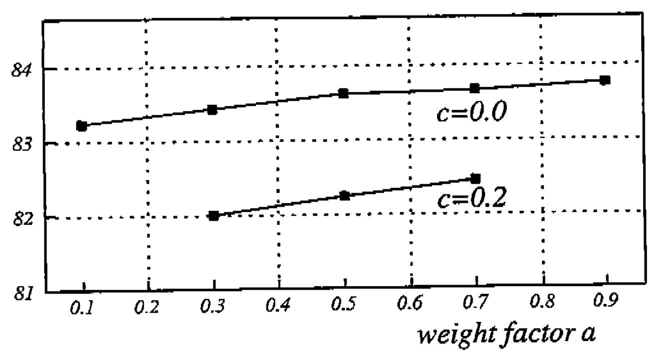

Fig. 5 *The volumetric efficiency as a function of the weight factors.*

- The thickness of the valve and thereby the mass become maximal instead of minimal. This is easily explained by recognising that the acceleration will be smaller for heavier valves.
- The maximum valvelift is significantly smaller since the time during which the acceleration takes place is smaller.
- The spring forces are larger since this will suppress the acceleration.
- Both efficiencies drop due to the smaller flow area and less accurate timing of the opening and closing of the valve.

One design ($a = 0.1, b = 0.7, c = 0.2$) shows a solution totally different from the others. The impact velocity and both efficiencies are very low, due to irrational valve dynamics (fig. 8). It appears that the gain in impact velocity justifies a great loss in isentropic efficiency. But the loss in volumetric efficiency is more dramatic, so the other designs with ($c = 0.2$) show more realistic efficiencies. For reasons of clarity, this design is ignored in some figures.

Symbol	$c = 0.0$					$c = 0.2$				Unit
a	0.1	0.3	0.5	0.7	0.9	0.1	0.3	0.5	0.7	-
b	0.9	0.7	0.5	0.3	0.1	0.7	0.5	0.3	0.1	-
D_v	205.7	205.4	219.1	202.6	199.2	239.9	205.2	212.8	205.8	mm
h_v	0.50	0.50	0.50	0.50	0.50	4.98	5.00	4.96	4.99	mm
x_{max}	2.56	2.31	2.19	2.20	2.15	1.99	2.02	1.93	1.93	mm
F_{max}	79.5	69.0	66.0	55.5	52.7	239.0	228.9	238.7	155.8	N
F_{min}	13.2	14.5	14.5	25.8	39.7	39.3	36.8	39.9	38.3	N
η	73.30	73.20	73.15	73.09	72.93	70.45	71.26	71.17	71.12	%
λ	83.23	83.43	83.62	83.66	83.76	79.84	82.00	82.24	82.45	%
v_{max}	5.08	4.85	4.76	4.74	4.54	1.41	1.72	1.63	1.71	m/s

Tab. 4 *The different optimal designs that resulted from the optimization by using different weight factors. For the left side the impact velocity vanishes from the objective function (c=0.0).*

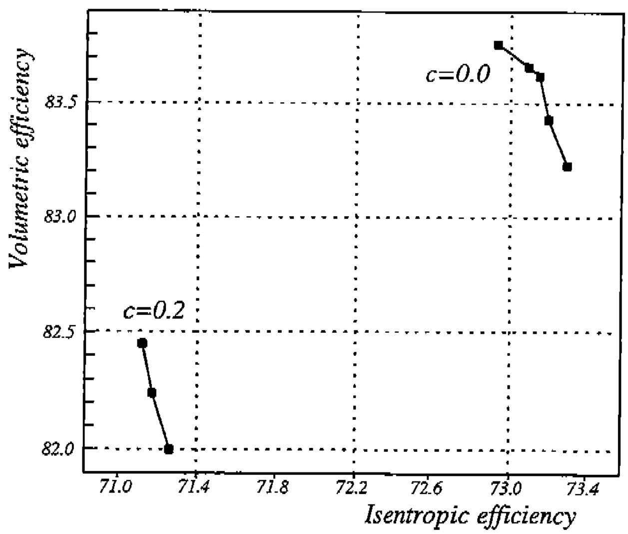

Fig. 6 *The volumetric efficiency as a function of the isentropic efficiency.*

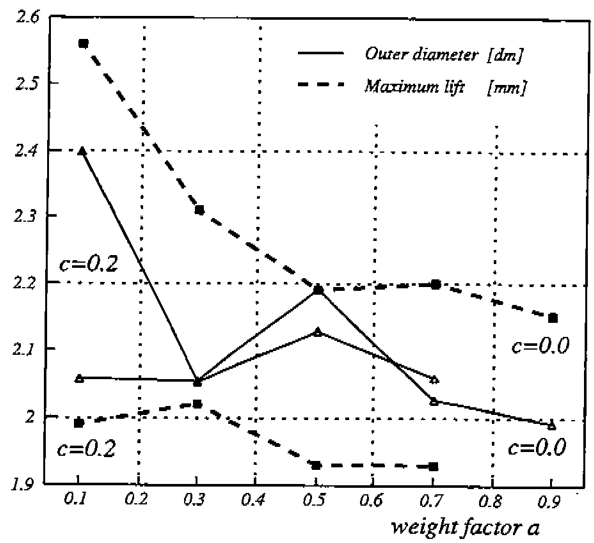

Fig. 7 *The values of the outer diameter and the maximum valve lift as a function of the weight factors.*

CONCLUSIONS

This project led to the following conclusions:

- The combination of the genetic algorithm with the compressor simulation and the generic model leads to an effective design tool. It is especially usefull when a considerable number of parameters is involved.
- Since the results are never better than the models used, experimental validation is needed. Further work on the generic and compressor model is recommendable.
- Low impact velocities, leading to a long lifespan of the valve, imply low efficiencies.

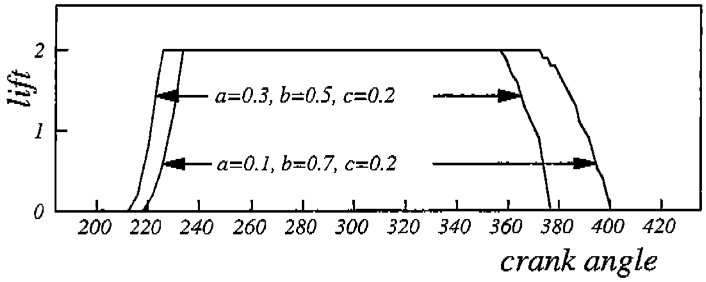

Fig. 8 *The suction valve according to the design for* $a = 0.1, b = 0.7, c = 0.2$ *opens late due to the large clearance volume and it closes 40° after the b.d.c. due its extensive mass. The latter explains the low isentropic efficiency for this design.*

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